A Development of Vehicle Damage Volume Recognition Algorithm based on Deep Learning Model

Min Htet Thar*, Man Zhang**, Dong Myung Lee**
*Research Team, EasyGeo Co., **Dept. of Computer Engineering, Tongmyong University
*htatmin332@gmail.com, **mandyz0216@gmail.com, **dmlee@tu.ac.kr

Abstract

The vehicle damage volume recognition algorithm based on based on deep learning model is proposed in this paper. The proposed algorithm consists of four models: the vehicle body parts detection model, the vehicle damage inspection model, the vehicle damage classification model and the vehicle damage volume level analysis model. The average accuracy for vehicle body parts model achieved at 98.6%, the average accuracy for vehicle damage inspection model achieved at 94.5%, and the average accuracy for vehicle damage classification model achieved at 95.8%.

I. INTRODUCTION

In some previous studies, deep learning model was used to identify vehicle damage, but it is still difficult to apply it in the real auto insurance claim settlement process. In most cases, it is difficult to determine the extent of the damage (repair costs) by identifying the vehicle damage type alone, as many damage types are similar. Under the same damage type, different maintenance costs will be incurred according to different damaged areas. Therefore, to improve this problem, this paper proposes the vehicle damage volume recognition algorithm based on four models [1-4].

II. PROPOSED ALGORITHM

2.1 Design Philosophies

The basic design idea of proposed algorithm mainly consists of four models [5-6].

- The proposed algorithm is designed using convolutional neural networks (CNN), you only look once (YOLO) model, vehicle dataset, and vehicle damage dataset [2-3].
- Datasets is built by Kaggle, COCO dataset and other sites.
- The dataset was preprocessed using data enhancement methods and each image in the dataset was tagged using image annotation tools.
- The dataset was trained using the pre-trained YOLO object detection model [3].
- The vehicle damage volume level analysis model was established as the data framework based on body parts, damage detection and damage grade.
- In the process of the proposed algorithm, all parts of the body are first detected, and then damage inspection and classification are carried out.
- All of these results are analyzed using data frames to determine the degree of damage, which is then used to estimate repair costs.

2.2 Proposed Algorithm

The proposed algorithm consists of four models such as the vehicle body parts detection model, the vehicle damage inspection model, the vehicle damage classification model and the vehicle damage volume level analysis model, it is shown in Fig. 1. The vehicle body parts detection model is used to detect vehicle body parts and the vehicle damage inspection model is used to check each vehicle body part for damage, respectively. The vehicle damage classification model checks the body parts such as scratches, dents, shatters, breaks, and smashed. The vehicle damage volume level analysis model analyzes the damage level using the type of damaged body parts, damaged part, and damaged class. The results of these four models are used as parameters to estimate the maintenance cost caused by vehicle damages [5].

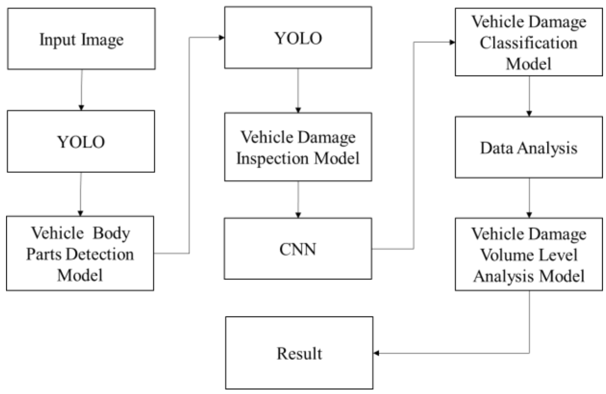

Fig. 1. Overview of proposed algorithm.

III. IMPLEMENTATION AND RESULTS ANALYSIS

In this paper, the vehicle body parts detection model, the vehicle damage detection model, and the vehicle damage classification model were implemented and tested among the four proposed models.

3.1 Datasets & Model Description

3.1.1 Datasets Collection

In the process of data collection, datasets for three models were collected through internet searches as shown in Table I.

TABLE I. DATASETS COLLECTION

Datasets	Sizes
Vehicle body parts datasets	2500 Images
Vehicle damage inspection datasets	1000 Images
Vehicle damage classification datasets	2500 Images

3.1.2 Datasets Labeling

Three datasets of three proposed models are labeled as shown as Table II such as 5 class labels of the vehicle body parts datasets, 2 class labels of vehicle damage inspection datasets, and 5 class labels of vehicle damage classification datasets.

TABLE II. LABEL CLASSES OF DATASETS FOR PROPOSED MODELS

Datasets for Proposed Models	Label_Classes
Vehicle body parts datasets	Front_Bumper
	Rear_Bumper
	Door
	Hood
	Lights
Vehicle damage inspection datasets	Damaged
	No_Damaged
Vehicle damage classification datasets	Scratches
	Broken
	Crush
	Dents
	Paint_Damage

3.1.3 Proposed Model Training

Each model was tuned and trained with traditional artificial intelligence (AI) framework and hyperparameters according to Table III. The testing environments for testing are described in Table IV.

TABLE III. TUNING AND TRAINING OF PROPOSED MODEL

Proposed Models	AI Framework	Hyperparameters
Vehicle body parts model	YOLOv5	Resize: 250x250
		Epoch: 100
		Batch_size: 16
		Optimizer: Adam
		Learning rate: 0.01
Vehicle damage inspection model	YOLOv5	Resize: 250x250
		Epoch: 100
		Batch_size: 16
		Optimizer: Adam
		Learning rate: 0.01
Vehicle damage classification model	CNN	Resize: 250x250
		Epoch: 100
		Batch_size: 16
		Optimizer: Adam
		Learning rate: 0.01

TABLE IV. TESTING ENVIRONMENTS

Resources	Specification
GPU	GeForce GTX 1050
Language	Python 3.7
OS	Window 10 64 bit
Machine Learning Libraries	TensorFlow 1.3.0 Keras 2.0.8 PyTorch 1.7

3.2 Model Evaluation

3.2.1 Testing Results

The proposed three models were tested using confusion matrix (CM) as shown in Fig. 2, and the results are shown in Table V, respectively. According to Table V, the average accuracy for vehicle body parts model achieved at 98.6%, the average accuracy for vehicle damage inspection model achieved at 94.5%, and the average accuracy for vehicle damage classification model achieved at 95.8%. As performance analysis, all models achieved above 90%.

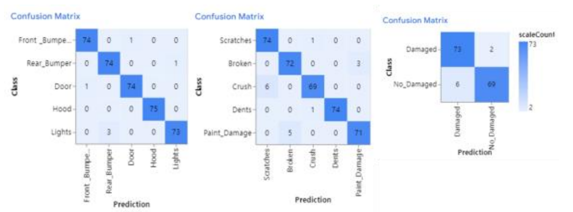

Fig. 2. Testing process of proposed three models.

3.2.2 Results Analysis

This is the positive results for the future implementation. if the size of the datasets is bigger, the data models will improve very well. Therefore, the performance analysis result of the proposed algorithm is expected to play a very positive role in research in the field of vehicle damage recognition.

TABLE V. PERFORMANCE EVALUATION OF PROPOSED 3 MODELS.

Proposed Model	Classes	Accuracy	Average
Vehicle body parts model	Front_Bumper	99.0%	98.6%
	Rear_Bumper	99.0%	
	Door	99.0%	
	Hood	100%	
	Lights	96.0%	
Vehicle damage inspection model	Damaged	97.0%	94.5%
	No Damaged	92.0%	
Vehicle damage classification model	Scratches	99.0%	95.8%
	Broken	96,0%	
	Crush	92.0%	
	Dents	99.0%	
	Paint_Damage	93.0%	

IV. CONCLUSION AND FUTURE WORKS

In this paper, we proposed the development of a vehicle damage recognition algorithm based on a deep learning model. As a result, the three data models achieved 98.6%, 94.5%, and 95.8%, respectively. However, the algorithm proposed in this paper has only been implemented about 1/3. The remaining two-thirds will be implemented soon. This study is expected to be very useful in the field of automating the auto insurance claim process and determining the extent of vehicle damage.

ACKNOWLEDGMENT

This research was supported by the BB21plus funded by Busan Metropolitan City and Busan Institute for Talent & Lifelong Education (BIT).

REFERENCES

[1] A. Shirode, T. Rathod, P. Wanjari, A. Halbe, “Car Damage Detection and Assessment Using CNN,” In Proc. 2022 IEEE Delhi Section Conference (DELCON), IEEE, pp.1-5, 11-13 Feb. 2022.

[2] K. Patil, M. Kulkarni, A. Sriraman, S. Karande, “Deep learning based car damage classification,” In Proc. 2017 16th IEEE international conference on machine learning and applications (ICMLA). IEEE, pp. 50-54, 18-21 Dec. 2017

[3] Liu, Yifan, Lu, BingHang, Peng, Jingyu, Zhang, Zihao, “Research on the use of YOLOv5 object detection algorithm in mask wearing recognition,” World Scientific Research Journal, pp.276-284, 2020.

[4] W. Zhang, et al., “Automatic Car Damage Assessment System: Reading and Understanding Videos as Professional Insurance Inspectors,” In Proc. AAAI Conference on Artificial Intelligence, vol.34 no. 09, pp.13646-13647, Apr. 2020.

[5] Min Htet Thar, Dong Myung Lee, “Vehicle Damage Volume and Traffic Accident Types Recognition Algorithm based on Mask Regional-CNN,” In Proc. 2022 KICS Winter Conference (ISSN: 2383-8302), KICS (Korea Information and Communications Society), vol. 77, pp.0436-0437, 2022. 02. 09-11.

[6] Min Htet Thar, Man Zhang, Gi Ho Nam, and Dong Myung Lee, “Vehicle Damage Volume Level Recognition Algorithm based on Convolution Neural Network and Yolo Model,” In Proc. 2022 International Conference on Communication and Computer Research (ICCR 2022), KICS (Korea Information and Communications Society), UCSY (University of Computer Studies, Yangon), Myanmar, ETRI (Electronics & Telecommunications Research Institute), 21-22 Nov. 2022.